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Towards the Development of a Global, Satellite-based. Terrestrial Snow Mission Planning Tool

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Bart Forman

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Observation Types

Objectiv

USSE

Hyperplanes Eulerian Grid Single Platforr Constellation

Machine Learning

Variability Experiments





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Observation Types

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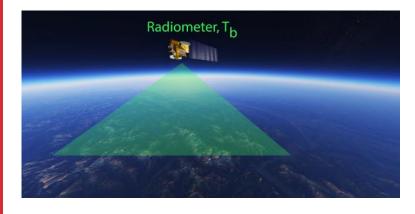
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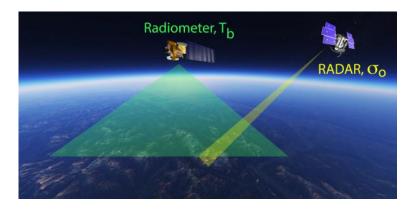
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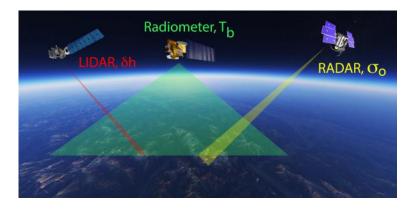
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Objectives

- 1 What observational records are needed (in space and time) to maximize terrestrial snow experimental utility?



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Conclusions

- What observational records are needed (in space and time) to maximize terrestrial snow experimental utility?
- 2 How might observations be coordinated (in space and time) to maximize this utility?
- What is the additional utility associated with an additional observation?
- 4 How can future mission costs be minimized while ensuring Science requirements are fulfilled?



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· ------ Nature Run Snow Depth & SWE over North America
LIS + MERRA2 - model-based representation



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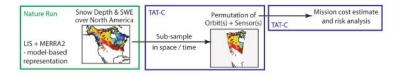
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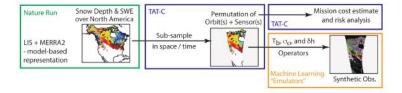
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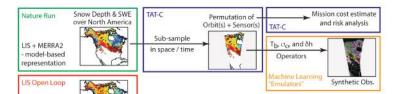
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Trade-off Spa

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LIS + GLDAS

apply representative B.C. error
 no assimilation (a.k.a., Open Loop)
 with assimilation (merge with observations from suite of sensors)





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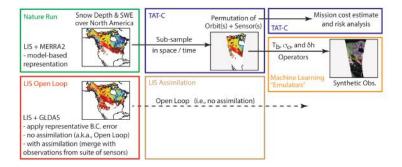
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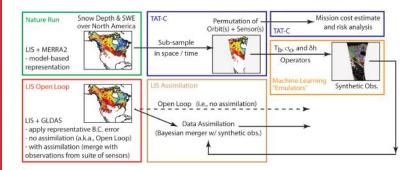
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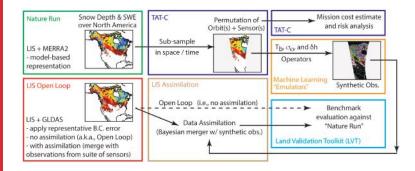
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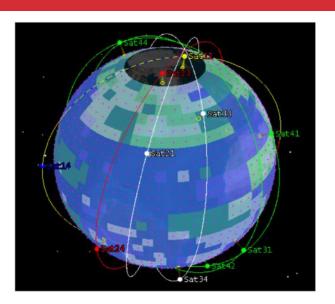
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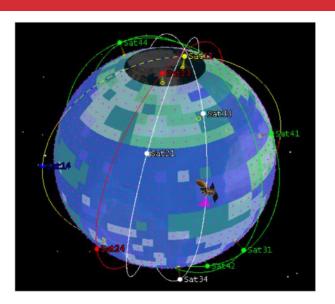
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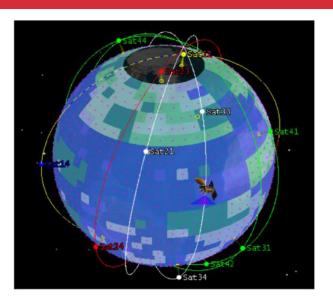
Experiment





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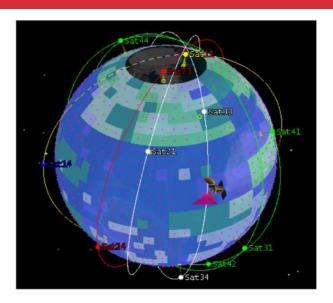
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"Comb" Viewing → Single Platform

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Trade-off Space: Coverage vs. Resolution

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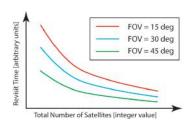
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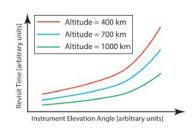
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Machine Learning Emulators

Experiments





- Explore trade-off between engineering and science
 - Field-of-View (FOV)?
 - Platform altitude?
 - Repeat cycle?
 - Single platform vs. constellation?
 - Orbital configuration(s)?
- How do we get the most scientific bang for our buck?



Machine Learning "Emulators"

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Land Surface Model(s)



Physically-based



Observation Operator (Forman et al., 2013; Forman and Reichle, 2014; Forman and Xue. 2016)



Multi-frequency, Multi-polarization **Training Targets**



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atmosphere T₂-meters vegetation Tskin LAI snow SWE $\rho(z)$ T(z)SLWC grain size soil Tsurf moisture

Physically-based Land Surface Model(s)



Observation Operator (Forman et al., 2013; Forman and Reichle, 2014; Forman and Xue. 2016)

spectral difference 18V - 36V 18H - 36H 10V - 36V 10H - 36H

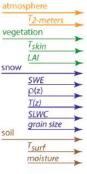
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Physically-based Land Surface Model(s)



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Multi-frequency, Multi-polarization **Training Targets**



Spatiotemporal Variability

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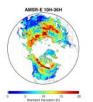
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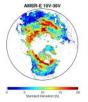
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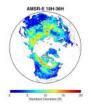
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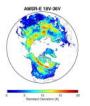
Emulators Variability

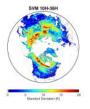
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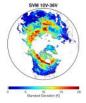


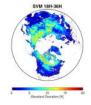


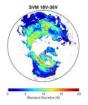














Spatiotemporal Variability

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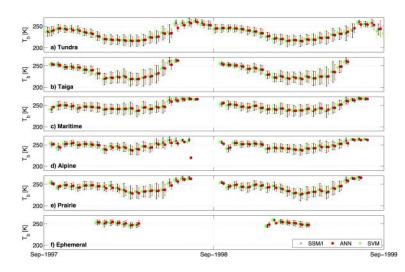
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Variability Experiment





Relevancy Scenarios

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Experiments

• Scenario 1: Benchmark Analysis

- Passive MW Assimilation only
- Scenario 2: Comparative Analysis
 - Passive MW vs. Active MW vs. LIDAR
- Scenario 3: Multi-sensor Analysis
 - single-sensor platform
 - multi-sensor platform
 - constellation of sensors



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- Global snow mission planning will require evidence of achievable science via OSSE
- Land Information System (LIS) provides "nature run" plus assimilation framework
- TAT-C provides spatiotemporal sub-sampling of observations, including cost estimates and risk assessments
- Machine learning maps model state(s) into observation space (i.e., T_b and σ_0)
 - ► Enables integration of T_b , σ_0 , and δh in geophysical realm (i.e. SWE and snow depth)
 - Multiple frequencies/polarizations/observations allow for flexibility and modularity in DA framework
- Snow OSSE is on-going → open to suggestions!



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Observation

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Conclusions

Thank You.

Questions and/or Comments?

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